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Probabilistic graphical models to deal with age estimation of living persons

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Abstract

Due to the rise of criminal, civil and administrative judicial situations involving people lacking valid identity documents, age estimation of living persons has become an important operational procedure for numerous forensic and medico-legal services worldwide. The chronological age of a given person is generally estimated from the observed degree of maturity of some selected physical attributes by means of statistical methods. However, their application in the forensic framework suffers from some conceptual and practical drawbacks, as recently claimed in the specialized literature. The aim of this paper is therefore to offer an alternative solution for overcoming these limits, by reiterating the utility of a probabilistic Bayesian approach for age estimation. This approach allows one to deal in a transparent way with the uncertainty surrounding the age estimation process and to produce all the relevant information in the form of posterior probability distribution about the chronological age of the person under investigation. Furthermore, this probability distribution can also be used for evaluating in a coherent way the possibility that the examined individual is younger or older than a given legal age threshold having a particular legal interest. The main novelty introduced by this work is the development of a probabilistic graphical model, i.e., a Bayesian network, for dealing with the problem at hand. The use of this kind of probabilistic tool can significantly facilitate the application of the proposed methodology: examples are presented based on data related to the ossification status of the medial clavicular epiphysis. The reliability and the advantages of this probabilistic tool are presented and discussed.

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1 Introduction

Determination of the age of individuals is crucial for the correct application of many penal, civil and administrative laws in numerous countries worldwide. However, there are many situations where this cannot be accomplished through formal means, such as valid identity documents. As an example, the numerous cases of border-crossing migration involving unaccompanied minors or persons lacking valid identity documents could be cited. Consequently, forensic age estimation of living people is nowadays an important and current practice for a large number of medico-legal or forensic services [1-5]. Examinations in this particular field are important for both estimating the chronological age (for example in case of adoption or other administrative issues) and evaluating the probability that the examined individual is younger or older than a given age threshold having a particular legal interest (such as the age of majority or the age of criminal responsibility). Often, the kind of answer one has to produce must be calibrated according to the demand of the juridical authority. The age thresholds of interest are country-specific and usually fall between 14 and 22 years of age [5]. Hence, it is important to avail oneself of medical methods which allow one to reliably discriminate ages around this interval.

The chronological age of an individual is generally estimated by the evaluation of the degree of maturity, or biological age, observed in some physical attributes, used as indicators of maturity [6,7]. These attributes are usually related to the dental and skeletal development, but also to changes in the secondary sexual characteristics [3,5]. For instance, the dental development could be assessed for evaluating the mineralization and the eruption of the teeth, while the skeletal development is generally associated with the ossification status of several ossification centers in the body [8-10]. Starting from these indicators, inference on the chronological age is performed in a two-step process: first, the degree of maturity of a given physical attribute is assessed and then the chronological age is estimated through chosen statistical methods. However, these latter suffer from several conceptual and statistical drawbacks. Statistical methods for the age estimation can be grouped into two general categories: on the one hand, the methods focus on the estimation of the chronological age of an individual, on the other, the methods classifying the individual into a meaningful class of age, for example the ages lower or higher than a given age threshold [11]. Methods which estimate the chronological age usually employ traditional regression models and polynomial functions [12-15] or descriptive statistics [16-19]. Typically, these methods provide a point estimate corresponding to the most likely age of the examined individual, as well as a related confidence interval [20]. From a statistical point of view, a confidence interval is not a representation of the distribution of the uncertainty about the estimated age; thus, there is a risk of misinterpreting the real meaning of this kind of statistic. In fact, because of their nature, these estimates are related to the concept of repeatability of a particular event and they are not a representation of the distribution of the uncertainty about the estimated age; hence it may not be an optimal statistic for forensic purposes [20].

Some of these drawbacks are circumvented by the methods which classify the examined individual according to a meaningful age interval. These methods have generally been developed for age assessment from data related to the dental maturity, but there is no reason for not applying them with data from other physical attributes. Some of them employ a logistic regressions model considering, as a dependent variable, the event that the examined subject is younger or older than a given age threshold [21,22]. However, these methods suffer from some other conceptual and statistical weaknesses, that are related to the use of the developmental stages as independent variables and thus consequently making a questionable assumption of their continuity [23-26]. Alternatively, other methods to this approach have been conceived in a Bayesian framework and they allow one to obtain the probabilities that an individual is younger or older than a given age threshold [11,26] or the probabilities that the age of the individual is included in a given age interval [23,27]. Although these methods provide the quantified probability that the chronological age of the examined individual is included in a given range, they do not allow the user to obtain an estimation of the age of the individual, a kind of information which may be interesting information for legal and juridical purposes. Ideally, it seems to be a desirable feature of a statistical method to produce these two pieces of evidence (i.e. an estimate of the chronological age and the probabilities that an individual is younger or older than an age threshold), which are dependent in nature, in a related and transparent way. Furthermore, if the observations coming from the examination of the individual need to be assessed in regard to different age thresholds, the numerical elements have to be estimated individually for each evaluation, and this could be impractical.

Finally, how could all the drawbacks briefly discussed in this Section be taken into consideration to produce useful elements for answering the main question related to the problem of age estimation of living persons? An optimal solution may be provided by the application of the Bayesian approach to produce a posterior probability distribution for the chronological age of the examined individual. Moreover, this posterior distribution can be used to compute posterior probabilities that the examined individual is either younger or older than a given age threshold of legal interest [20,28].

Therefore the objective of this article is to further iterate the validity of the probabilistic Bayesian approach for both (a) estimating the age of living people, and (b) discriminating between two propositions of interest related to the event that a person is younger (or older) than a given legal threshold. The main novelty introduced in the paper is the use of a Bayesian network, a probabilistic tool describing variables of interest and their respective probabilistic relationships and allowing the user to probabilistically infer the age from data, notably, the observation of the degree of maturity of a given physical attribute. The employment of this kind of tool has already been previously proved to offer huge advantages for both practical application of the Bayesian approach and the expansion of the inferential reasoning for taking account of some factors which could influence age estimation [29,30].

The present paper is structured as follows. Section 2 presents a hypothetical scenario and deals with the theoretical background and the current methods for age estimation. In Section 3 the Bayesian probabilistic approach is described. In Section 4 a Bayesian network for age estimation is explained and its practical applications are illustrated in the Section 5. Discussion and conclusion will be presented in Sections 6 and 7.

2 Illustrative case example

2.1 Hypothetical illustrative scenario

Suppose that, for some legal reasons, an examination for the age estimation of a living young male adult is demanded by a juridical authority. For the sake of illustration, let us suppose two distinct scenarios: in the first one, suppose that the juridical authority is interested in knowing the chronological age of the examined person, while in the second scenario the examination is demanded for determining whether the individual has or has not passed the legal age of majority, for example 18 years of age, following the Swiss civil code[1]. Examinations are performed by experienced medico-legal specialists following the recommendations of the Study Group on Forensic Age Diagnostic (AGFAD) [31]. The anthropometric measures and the assessment of the secondary sexual characteristics are performed during a preliminary physical/medical examination. No signs of developmental disorders are noticed. Then a dental examination is also performed, with specific interest to the observation of the third molar mineralisation. Finally, the skeletal development is assessed by a radiographic examination of the left hand as well as an assessment of the ossification status of the medial epiphysis of the clavicle by means of a computerised tomography scan (CT-scan).

2.2 The assessment of the degree of maturity

[1] The English version of the Swiss Civil code can be read at the following internet address: http://www.admin.ch/ch/e/rs/2/210.en.pdf (last access: 04th of February 2015)

The task for an examiner consists of assessing the degree of maturity observed during the examination of each physical attribute. This assessment is usually performed by classifying the degree of maturity observed in categorical developmental stages or by means of a referenced atlas, although this latter may be seen as a categorical classification in which each reference corresponds to a developmental stage. This kind of categorical assessment is needed because of the difficulty or even the practical impossibility of evaluating the degree of maturity on a continuous scale [32]. Many classifications may exist for a given physical attribute and, usually, key elements to observe for assigning a given developmental stage are defined in a visual and/or descriptive manner [8-10,33]. To illustrate this, let us consider the previous case example and for the sake of simplicity let us focus only on the examination of the medial clavicle. Suppose that the examiner observes in the CT-scan image a partial union of the medial clavicular epiphysis which is compatible with the ossification status defined in the third stage of a traditional four-stage classification [34,35]. Therefore, he classifies its observation in this specific stage. Then the following and final step in the process of age estimation consists of translating this degree of maturity observed into an estimated chronological age or in the probabilities that the examined individual is younger or older than a given age threshold, by means of some statistical methods which are generally specific for a given physical attribute.

2.3 Current methodologies applied to the scenario

Considering the previous hypothetical scenario, the assessment of the ossification status of the medial clavicular epiphyses in the third stage of the employed classification allows the estimation to be a mean age of 20.9 years, with an associated 95% confidence interval from 16.5 to 25.5 years [34]. However, this result presents some statistical and practical drawbacks. As already quoted in the Section 1, this kind of interval is unsuitable for the assessment of the uncertainty for forensic purpose. Moreover, from a practical point of view, such a result is not very helpful for discriminating whether the examined individual is younger or older than 18 years of age. In fact, this age threshold is included into the estimated 95% confidence interval and this kind of statistic does not allow one to evaluate which one of the two possibilities is more likely [20].

3 A Bayesian approach to interpreting the data

The rationale behind the application of the Bayesian approach for age estimation is very intuitive, and could be described as an updated procedure of the initial beliefs about some given propositions (which may concern, for example, the chronological age of a subject) into posterior beliefs following the observation of given evidential elements (e.g., the developmental stages of the physical attribute belonging to that subject). This procedure is formally described by Bayes' Theorem and it is followed intuitively and naturally by the medico-legal examiners for age estimation of an individual. Thus, if the chronological age is considered as a continuous variable and the degree of maturity is assessed in categorical developmental stages, the Bayes' Theorem can be expressed as follow:

$$f_A(a|C = s_i) = \frac{\Pr(C = s_i|A = a) \times f_A(a)}{\Pr(C = s_i)} \tag{1}$$

where $f_A(a|\ C=s_i)$ is the posterior distribution on the chronological age given the observed developmental stage s_i, $\Pr(C=s_i|A=a)$ is the probability that the physical attribute C has reached the ith developmental stage s, knowing the chronological age and $f_A(a)$ is the prior distribution of the chronological age. The probability in the stage (i.e., $\Pr(C = s_i)$) can be further expanded using the law of total probability [36]:

$$\Pr(C = s_i) = \int_A \Pr(C = s_i|A = a) \times f_A(a)da \tag{2}$$

This posterior probability distribution on the chronological age can then be used for computing the probabilities to be younger or older than a given age threshold [20,28]. Let us recall the previous hypothetical scenario and suppose that the juridical authority is interested in knowing if the examined individual is younger or older than 18 years of age. These two possibilities can be rewritten in the form of two mutually exclusive propositions, for example:

- H_1: the examined individual is older than 18 years of age.
- H_2: the examined individual is younger than 18 years of age.

Thus, the probability that the examined individual is older than 18 years of age knowing that the ith developmental stage has been observed for the physical attribute C can be computed as follows:

$$Pr(H_1|C = s_i) = \int_{18}^{m} f_A(a|C = s_i)da = \int_{18}^{m} \frac{\Pr(C = s_i|A = a) \times f_A(a)da}{\int_A \Pr(C = s_i|A = a) \times f_A(a)da} \tag{3}$$

where m is the maximal age which can be reasonable to consider in a lifetime. Posterior probability for H_2 can be computed similarly.

In order to quantify how the observation of a given degree of maturity in a physical attribute helps in discriminating between the two propositions of interests and thus in evaluating if the examined individual is younger or older than 18 years of age, the use of the posterior odds may be extremely helpful. The posterior odds in favour of the first proposition can be computed as follow [36]:

$$O(H_1|C = s_i) = \frac{\Pr(H_1|C = s_i)}{\Pr(H_2|C = s_i)} = \frac{\int_{18}^{m} f_A(a|C = s_i)da}{\int_{0}^{18} f_A(a|C = s_i)da}$$
$$= \frac{\int_{18}^{m} \frac{\Pr(C = s_i|A = a) \times f_A(a)da}{\int_A \Pr(C = s_i|A = a) \times f_A(a)da}}{\int_{0}^{18} \frac{\Pr(C = s_i|A = a) \times f_A(a)dA}{\int_A \Pr(C = s_i|A = a) \times f_A(a)da}} \quad (4)$$

Then, considering that the denominators of the two components of the last ratio in the Equation (4) are identical constants, they can be simplified as thus:

$$O(H_1|C = s_i) = \frac{\int_{18}^{m} \Pr(C = s_i|A = a) \times f_A(a)da}{\int_{0}^{18} \Pr(C = s_i|A = a) \times f_A(a)da} \quad (5)$$

The *posterior odds* are a transparent and easily interpretable measure for expressing a decision using the observed evidence: if the ratio is greater than one, then the observed evidence (i.e., the degree of maturity observed for a given physical attribute) corroborates the first proposition (i.e., the examined individual is older than 18 years of age), so that H_1 is more probable, and vice versa. The value of the odds, then, indicates the how much a proposition is more likely compared with the other one. Therefore, the posterior odds may be an optimal tool for expressing decisional results of an examination for evaluating the possibility that an individual is younger or older than a given age threshold. In order to simplify the application of the aforementioned approach, the model can be encapsulated in a probabilistic graphical tool, namely a Bayesian network.

4 A Bayesian network for age estimation[2]

4.1 Bayesian networks

[2] Further details on the network construction are available by contacting the authors.

Bayesian networks are probabilistic graphical models joining both representational (*qualitative*) and computational (*quantitative*) aspects. These probabilistic tools allow one to model complex events in situations of uncertainty by thinking in graphical terms about dependencies between relevant variables in a scenario of interest. Once the model is built, the network allows inferring about the probability of an unobserved variable by instantiating knowledge about one or more observed states of variables. Elements that compose Bayesian networks are therefore *nodes*, which represent the variables, and *directed arrows*, which connect the nodes showing the existing probabilistic dependence relationships between them. These elements are combined to form the *Directed Acyclic Graph*, (i.e., a graph in which no loops are allowed). Each node is characterised by a range of mutually exclusive *states*, representing the possible outcomes that the variable can assume. In order to allow the user to perform inferences, a set of probabilities is specified for each state of a variable, by means of a *Conditional Probability Table* (*CPT*) [29,30]. Bayesian networks are widely exploited in forensic science as well as in medicine [30,37] and thus, it seems especially interesting to apply this probabilistic tool in the field of legal or forensic medicine.

4.2 Basic Structure of a Bayesian network for age estimation

For implementing the Bayesian network, the Hugin software was used in this work[3]. The principal elements of interest related to inferential reasoning underlying age estimation are contained in Equation (1). Consequently, starting from this equation it is easy to build a graphical model. The variables, which have to be considered, are mainly the chronological age and the degree of maturity, expressed in categorical developmental stages. Thus, these two elements could be represented by two nodes, respectively "A" and "C=s_i" as illustrated in Figure 1. The two nodes are linked by an arrow going from the node "A" to the node "C=s_i" to reflect their biological and probabilistic dependency. For allowing the user to evaluate the probability that the examined individual is younger or older an age threshold directly in the network, it may also be interesting to add to the network a node "H" representing the propositions of interest, H_1, the examined individual is older than 18 years of age, and H_2, the examined individual is younger than 18 years of age. Taking into consideration that the proposition's intervals add up to some chronological age, it seems to be logical that the node "H" graphically depends on the node "A" (Figure 1).

The *states* of the nodes are closely related to the nature of the variable outcomes that they represent. Hence, "H" assumes two states, "C=s_i" a number of states corresponding to the number of stages of classification considered (i.e., four states for a four-stage classification) and "A" a set of values which

[3] A free demonstrative version of this software –Hugin Lite– is available on the website www.hugin.com.

cover the age range which would be considered in the age estimation. Note that the implementation of continuous variables may be very tedious depending on the software used. In this case, a solution could be to discretize the variable into a set of consecutive disjoint intervals which cover the range of value representing all the possible outcomes [29,38]. Thus in the present case, the states of the "A" node are defined as an interval representing a span of life days (i.e. each interval has a unit value of 1/365). Details on the nature of the nodes as implemented are shown in Table 1.

Once the qualitative structure of the network is built, it is possible to reason about the probabilities which are associated to each node through the CPTs.

4.3 Probability assessment in the Bayesian network for age estimation

The probabilities assigned in the CPTs of the network reflect the initial belief that one may have about the respective variables modelled. Thus, for example, the probabilities entered in the CPT of the node "A" are the *prior probability* on the chronological age, (i.e., $f_A(a)$ in the Equations above). These probabilities should reflect the initial belief that an examiner may have about the chronological age of the examined individual, based on personal knowledge or past experience. These probabilities may be assigned through a comparative observation of underlying biological similarity existing between the examined individual and other individuals of known age [20] or, alternatively, one could also choose a distribution reflecting the chronological ages of the individuals of whom an examination might be needed. This second methodology has been chosen in this work.

In the hypothetical scenario presented above the examination is performed on a young adult. One might believe that in such situations, the distribution of individuals for whom an examination for age estimation purpose is requested may be close to the age threshold of interest, for example 18 years of age. In this context, persons much younger or older than 18 years of age would not be examined, because it should be clear that their age is not close to this particular age. Examination would rather be carried out on individuals for whom the age can be questioned, and it seems logical that the ages of these individuals are dispersed around the 18 years of age.

Furthermore, since being declared minor presents some advantages in civil and penal juridical context, one may also believe that the dispersion around this age threshold is not symmetric, reflecting the fact that, probably, there is a predominance of persons older than 18 years of age for whom an examination for age estimation is requested, because for them, it is advantageous to claim being younger than this age threshold. This initial belief can be expressed in probabilistic terms for example with a Skew-Normal distribution with a location parameter of 15, a scale parameter of 8 and a slant parameter of 6, $\mathcal{SN}$(ξ=15, ω=8, α=6) (Figure 2) [39], which is the prior distribution on the chronological age used for examples in this paper.

The CPT of the node “H” is then complied in order to simply subdivide the probability distribution assigned to the node “A” according to the two different age intervals of interest, i.e., the age lower than 18 years of age and those higher than 18 years of age. Note that beliefs in the states of “H” are automatically updated when the prior distribution in “A” is varied.

Finally, the probabilities assessed for compiling in the CPT of the node “C=s_i” are the probabilities of observing a given developmental stage knowing the chronological age (i.e., $\Pr(C = s_i|A = a)$ in the expression presented in the Section 5). In this work, these probabilities are assessed by means of *transition analysis,* a parametric method for modelling the “age-at-transition”, an unobserved latent variable describing the average age at which individuals in a given population move from a developmental stage to the next higher one in an ordered sequence [40]. Transition analysis was developed in the anthropological fields for age estimation of skeletal remains and it is dependent on two assumptions, namely, the independence of each developmental stage from others, knowing the age, and the absolute unidirectionality of the morphological changes without any overlapping [40]. Generally, the classification systems used for assessing the degree of maturity of the physical attributes exploited for the age estimation of living persons meet with these assumptions, thus this method can be applied in this context and can be an extremely powerful tool associated with the Bayesian networks.

For assigning the probabilities of interest, transition analysis employs regression models conceived for dealing with categorical variables, such as logit or probit models [40,41]. For compiling the CPT of the node “C=s_i” of the network presented in this paper, a *continuation ratio model* with a logit link has been used [40,42]. In the context of age estimation, the continuation ratio model can be described as follows [42]:

$$Pr(C = s_i | C \geq s_i, A = a_j) = \digamma(\alpha_i - \beta_i a_j) \quad (6)$$

where α_i and β_i are, respectively, the intercept and the slope of the regression curves to be estimated. $\digamma$ is the link function related to the regression model, in this case a logistic distribution. The probability of the stage given the chronological age can then be computed as follows [42]:

$$Pr(C = s_i|A = a) = Pr\big(C = s_i\big|C \geq s_i, A = a\big) \prod_{r=1}^{i-1} Pr(C > s_r|C \geq s_r, A = a)$$
$$= \digamma(\alpha_i - \beta_i a) \prod_{r=1}^{i-1} \big(1 - \digamma(\alpha_r - \beta_r a)\big) \quad (7)$$

In all the equations presented above, *i* can take the value from *1* to *4*, 4 being the number of developmental stages of the classification adopted in the data sample used for the analysis on this work. To facilitate the compilation of the CPTs, Bayesian network software allows the user to create some useful expressions. For example, Equation (7) can be directly written in the CPT of the node "C=s_i" simplifying its compilation which is then done automatically by the software (see *note 5*).

5 Practical application of the Bayesian network in the hypothetical scenario

5.1 Estimation of the parameters of transition analysis

For a practical application, transition analysis should logically be applied to a reference sample adapted for the evaluation of the observations made during the examination of a given individual. For the illustrative purpose of this paper and for the sake of transparency, the database presented by Kreitner *et al.* [34] has been used. The data sample consists of 380 individuals (229 males and 151 females) who cover a range of ages form 0 to 30 years. It reports the assessment of the degree of maturity observed through a CT-scan examination of the medial clavicle following a traditional four-stage classification. The ages of the subjects are reported in years in the data sample. For the application of transition analysis, subjects presented in heterogeneous groups of ages (i.e., 0-4 and 5-9) are assigned at the maximal age of the range (i.e., 4 and 9 years of age). The statistical analysis was performed with the VGAM (Vector Generalized Linear and Additive Models) package of the statistical software "R"[4] [43]. The results of transition analysis are shown in Table 2.

The value presented in the Table 2 can then be used for completing the Equation (7) and the expression in the software language for automatically filling in the CPT of the node "C=s_i" for the age estimation[5].

[4] R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Wien, Austria. URL: http://www.R-project.org/.

[5] The expression used to compile the CPT of the node "C=s_i" is the following in the Hugin language: *Distribution (1 / (1 + exp (-(18.39 - 1.35 * A))), 1 / (1 + exp (-(21.12 - 1.17 * A))) * (1 - 1 / (1 + exp (-(18.39 - 1.35 * A)))), 1 / (1 + exp (-(30.72 - 1.30 * A))) * (1 - 1 / (1 + exp (-(18.39 - 1.35 * A)))) * (1 - 1 / (1 + exp (-(21.12 - 1.17 * A)))), (1 - 1 / (1 + exp (-(30.72 - 1.30 * A)))) * (1 - 1 / (1 + exp (-(18.39 - 1.35 * A)))) * (1 - 1 / (1 + exp (-(21.12 - 1.17 * A))))).*

5.2 Application of the Bayesian network in the hypothetical scenario

In the previous scenario, the examiner associated the ossification status of the medial clavicular epiphysis with the third stage of the employed classification. This evidence can be easily entered in the network, simply be instantiating the state "Stage 3" of the node "$C=s_i$" and then, the probabilities associated at the other nodes in the network are automatically updated through Bayes' Theorem. Finally, the posterior probability distribution on the chronological age can be read in the node "A", while the posterior probabilities on the two propositions of interest are visible in the node "H" (Figure 3a).

Consider again the hypothetical scenario and suppose that the juridical authority has requested an estimation of the chronological age. Then, the posterior probability distribution on the chronological age available in the node "A" can be used, for example, for computing a 95% Highest Posterior Density (HPD) interval, which includes, in this case, a range of 16.61 to 24.27 years of age (Figure 4a). This kind of interval is an optimal and transparent estimate for the chronological age and it defines the interval in which there is a 0.95 probability of containing the true value of the variable of interest, in this case the chronological age [44].

If the juridical authority is rather interested in evaluating the possibility that the examined individual is younger or older than 18 years of age, the posterior probabilities of the two propositions of interest can easily be read in the node "H" (Figure 3a). These probabilities can be used for computing the posterior odds in favour of the first proposition as showed in Equation (4):

$$O(H_1|C=s_3) = \frac{\Pr(H_1|C=s_3)}{\Pr(H_2|C=s_3)} = \frac{0.8806}{0.1194} = 7.38 \tag{8}$$

This means that the probability that the individual is older than 18 years of age is about 0.88 and that it is about seven times more probable that the subject examined is older than 18 years of age, knowing that the observed degree of maturity of the medial clavicular epiphysis corresponds to the third stage of a four-stage classification.

Thus, once the Bayesian network has been built, the probabilities of interest can be obtained in an extremely easy and rapid way. Furthermore, it can then be used in a routine without the need of further computation. Let us suppose that the juridical authority requests a second examination for another young adult male. This time, the experienced examiner observes in the CT-scan image of the collar bones a non-union but a detectable ossification of the epiphysis and therefore he classifies this observation in the second stage of a traditional four-stage classification [34,35]. Supposing that the data sample used for the transition analysis in the first case is also adapted for the evaluation of the observation coming from the second individual, then the results of interest can easily be obtained simply by entering the new evidence in the network by instantiating this time the state “Stage 2” in the node “C=s_i” of the network. The updated probabilities are observable in the other nodes of the network (Figure 3b). Then, the 95% HPD interval can be computed from the posterior probability distribution obtained from the node “A” (Figure 4b), and in this case the interval is included in a range of age from 13.81 to 19.71 years. Otherwise, the posterior odds can be computed from the posterior probabilities on the propositions in the node “H”:

$$O(H_1|C=s_2)=\frac{\Pr(H_1|C=s_2)}{\Pr(H_2|C=s_2)}=\frac{0.1930}{0.8070}=0.24 \tag{9}$$

That means that there is a probability of about 0.8 that the examined individual is younger than 18 years of age and that it is about four times (i.e., 1/0.24=4.167) more probable that he is younger than 18 years of age rather than older, knowing that the observed degree of maturity of the medial clavicular epiphysis corresponds to the second stage of a four-stage classification.

5.3 Validation of the Bayesian network for Age Estimation

Before applying a Bayesian network, it is important to guarantee that the results obtained by using it are correct. A possible way for validating a Bayesian network which has been built from an analytical expression is to compare the results obtained in the analytical way and those obtained with the network [30]. Thus, using Equations (5) and (7), it is possible to compute the posterior odds in favour of the proposition that the examined individual is older than 18 years of age and then compare the results obtained with those produced in Section 7.2 (Equations (8) and (9)). For the case where the third stage has been assigned at the observation performed by the examiner, the following result is obtained:

$$\begin{aligned}
O(H_1|C=s_3) &= \frac{\int_{18}^{m}\left[\digamma(\alpha_3-\beta_3 a)\prod_{r=1}^{2}\left(1-\digamma(\alpha_r-\beta_r a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\digamma(\alpha_3-\beta_3 a)\prod_{r=1}^{2}\left(1-\digamma(\alpha_r-\beta_r a)\right)\right]\times f_A(a)da}\\
&= \frac{\int_{18}^{m}\left[\digamma(\alpha_3-\beta_3 a)\times\left(1-\digamma(\alpha_2-\beta_2 a)\right)\times\left(1-\digamma(\alpha_1-\beta_1 a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\digamma(\alpha_3-\beta_3 a)\times\left(1-\digamma(\alpha_2-\beta_2 a)\right)\times\left(1-\digamma(\alpha_1-\beta_1 a)\right)\right]\times f_A(a)da}\\
&= \frac{\int_{18}^{m}\left[\digamma(30.72-1.30a)\times\left(1-\digamma(21.12-1.17a)\right)\times\left(1-\digamma(18.39-1.35a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\digamma(30.72-1.30a)\times\left(1-\digamma(21.12-1.17a)\right)\times\left(1-\digamma(18.39-1.35a)\right)\right]\times f_A(a)da}\\
&= \frac{0.8806}{0.1194}=7.38
\end{aligned} \tag{10}$$

by using, as prior distribution for the chronological age (i.e., $f_A(a)$), a Skew-Normal distribution $\mathcal{SN}$(ξ=15, ω=8, α=6).

For the case where the second stage was assigned instead, the result is:

$$
\begin{aligned}
O(H_1|C=s_2) &= \frac{\int_{18}^{m}\left[\mathrm{F}(\alpha_2-\beta_2 a)\prod_{r=1}^{1}\left(1-\mathrm{F}(\alpha_r-\beta_r a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\mathrm{F}(\alpha_2-\beta_2 a)\prod_{r=1}^{1}\left(1-\mathrm{F}(\alpha_r-\beta_r a)\right)\right]\times f_A(a)da} \\
&= \frac{\int_{18}^{m}\left[\mathrm{F}(\alpha_2-\beta_2 a)\times\left(1-\mathrm{F}(\alpha_1-\beta_1 a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\mathrm{F}(\alpha_2-\beta_2 a)\times\left(1-\mathrm{F}(\alpha_1-\beta_1 a)\right)\right]\times f_A(a)da} \\
&= \frac{\int_{18}^{m}\left[\mathrm{F}(21.12-1.17a)\times\left(1-\mathrm{F}(18.39-1.35a)\right)\right]\times f_A(a)da}{\int_{0}^{18}\left[\mathrm{F}(21.12-1.17a)\times\left(1-\mathrm{F}(18.39-1.35a)\right)\right]\times f_A(a)da} = \frac{0.1930}{0.8070} \\
&= 0.24
\end{aligned} \qquad (11)
$$

by using the same prior distribution for the chronological age as above.

Thus, comparing the values obtained with the Bayesian network (see Equations (8) and (9)) with those obtained in an analytical way (Equations (10) and (11) above), it is possible to verify that the results are the same.

6 Extended structure of the Bayesian network for age estimation

Flexibility is a key element of Bayesian networks: other relevant nodes can easily be added to the basic structure of the network in order to model more complex situations. Considering the Bayesian network presented above, it may be extremely useful for practical use to model the regression parameters obtained with transition analysis as independent nodes. These nodes can be related to the node "C=s_i" as shown in Figure 5. The expression in the node "C=s_i" can then take into account the state of the parameters' nodes rather than the estimated values of the parameters[6]: in that way, changes in the parameters are easier to integrate into the network. This new structure has operational advantages and can be extended to the definition of the prior of the chronological age. For example, three nodes modeling the parameters of the Skew-Normal distribution can be added to the structure of the network. These allow the user to define the prior distribution of choice by entering into the network the desired value of each parameter (Figure 5) [45]. The CPT of the node "A" is compiled in order to take into account the different combination of the parameters of the Skew-Normal distribution, in order to provide the distribution of choice according to the entered evidence (Figure

[6] The expression used for the node "C=s_i" became: *Distribution (1 / (1 + exp (-(α₁ - β₁ * A))), 1 / (1 + exp (-(α₂ – β₂ * A))) * (1 - 1 / (1 + exp (-(α₁ – β₁ * A)))), 1 / (1 + exp (-(α₃ – β₃ * A))) * (1 - 1 / (1 + exp (-(α1 – β₁ * A)))) * (1 - 1 / (1 + exp (-(α₂ – β₂ * A)))), (1 - 1 / (1 + exp (-(α₃ – β₃ * A)))) * (1 - 1 / (1 + exp (-(α₁ – β₁ * A)))) * (1 - 1 / (1 + exp (-(α₂ – β₂ * A))))).*

5). This kind of structure is ideal for performing further analysis, such as sensitivity analysis on the prior distribution. Alternatively, supposing that the user is interested in assigning different prior distributions, a further node can also be added: the states of the node may consist of a list of distributions that the user may choose. In this case, the CPT of the node “A” is compiled in order to assign as prior distribution of the chronological age the distribution instantiated in the network by the user.

Details on the nature and the states of the added nodes are shown in Table 3. Extended networks could also take into account factors influencing age estimation, such as sex, ethnical origin or socio-economic status of the examined individual [7]. Obviously, probabilities related to the added variables have to be assigned in the Bayesian network, for example, by using reference samples which include the variables of interests (e.g., the sample also contains information about the sex of the individuals [11]).

7 Discussion

The application of a probabilistic Bayesian approach is extremely suited for needs of the forensic age estimation of living persons. In fact, this kind of approach allows the expert to coherently deal with the uncertainty related to the process of the estimation, in order to provide transparent and demonstrable results which are necessary in juridical and legal context [20]. The model presented in this work allows one to produce a posterior probability distribution on the chronological age, which is an optimal, coherent and transparent representation of uncertainty related to the estimated variable, because it encapsulates all the knowledge about the parameters [20]. A credible interval on the chronological age, for example a 95% Highest Posterior Density interval, can also be assigned. This kind of interval is ideal for forensic and medico-legal purposes, because it describes the probability of the parameter of interest (i.e., the chronological age), as being effectively included into the range of the interval, given all the available information [44]. Furthermore, the posterior distribution on the chronological age can be used to quantify the posterior probabilities for two exclusive propositions describing the propositions of interest (i.e., that the examined individual is older, or younger, than a given legal age threshold). These two pieces of information (i.e. the posterior probability distribution on the chronological age and the posterior probabilities on the propositions of interests) are both fundamentals for forensic and medico-legal inferences as well as for the juridical decision-making process.

The practical application of the Bayesian approach is greatly facilitated by using graphical models. Bayesian networks, as a probabilistic tool, are excellent for modeling a probabilistic procedure for the evaluation and interpretation of evidence in the forensic framework [29,30]. They offer a transparent framework for the problem at hand by describing the probabilistic relationships between variables involved in the age estimation process and easing the practical routine application of the model. The Bayesian network for age estimation presented in this work allows the user to simultaneously obtain an estimate of the chronological age (by means of the posterior probability distribution) and the posterior probabilities that the examined individual is older or younger than a given age threshold of legal interest. The dynamic nature of the model allows one to easily vary this age threshold: this operation does not require any supplementary statistical analysis and this guarantees an extreme flexibility in the choice of the exclusive propositions in regard to the legal age threshold, which may be extremely helpful in practical application.

It is important to highlight that the posterior probability distribution is logically influenced by the choice of the prior probability of the chronological age. Although this may be seen by some quarters as an obstacle for the application of the proposed approach, the prior is, in fact, essential but natural information. Prior probability simply describes the initial belief of the examiner about the chronological age of the examined individual based on available background information. Discussion on this specific aspect can be found in Lucy [20] and Howson [46]. In this work, a distribution modeling the dispersion of the age around the age of 18 has been employed as prior distribution on the chronological age. However, in other cases the juridical authority may be interested in knowing whether the examined individual has or has not passed another age threshold, such 14 years of age: in this case, it may be preferable to choose a distribution modeling the age dispersion around this age threshold, rather than 18 years of age. Otherwise, one may prefer to assign the prior probability onto the propositions of interest rather than onto the chronological age: once more, the employment of the Bayesian network facilitates this kind of assessment, which can be tedious to perform in the analytical way.

For the purpose of illustration, the application of the model has been shown through examples related to the ossification status of the medial clavicular epiphysis. Following the AGFAD recommendations, examination of this physical attribute should be carried out if the skeletal development of the hand is completed [31], even though the assessment of the ossification status of the collar bones could be helpful for determining if an individual is younger or older than 18 years of age [10], as in the hypothetical scenario described above. This particular physical attribute has been chosen here for sake of simplicity, considering that its ossification status is classified into few stages, for example four in the four-stage classification applied in the data sample presented by Kreitner *et al.* [34], although this feature is not really suitable for producing an estimate of the age, because logically a large range of ages is associated with each stage and then the observation of a given stage does not allow the best discrimination across the age range. Nowadays this problem may be avoided by using more developed classifications which have been presented in scientific literature [17,19]. In this work, clavicle data has been used, but the application of this model can easily be extended to numerous other physical attributes, because of the use of transition analysis for the assessment of the probability of the stage given the age. Transition analysis refers to a regression model specific for ordinal categorical data; hence the proposed approach can be extended to all categorical classification of the degree of maturity. This is an extremely interesting feature of the model, considering that such classifications are employed for a large number of physical attributes involved in age estimation problems in living persons [8-10,33]. Since the examination of several physical attributes on the same given person is highly recommended for improving the quality of age estimation [31,47-49], the opportunity to apply the same approach for all the indicators is highly relevant. On one hand, this would standardise evaluative procedures by offering a sound scientific conclusion for a court of law. On the other hand, the opportunity to provide coherent results from different examinations may allow further developing of the model for a multi-traits evaluation. As seems to be logical, the development of a given physical attribute would not be completely independent of that of other attributes. Thus, methods for simultaneously evaluating, in a unique form, observations from various physical attributes (e.g., those recommended by the AGFAD) are extremely relevant and necessary. The employment of a model applicable within a large set of physical attributes, such as the Bayesian approach presented in this work, is already a first step in this promising direction. Furthermore, the use of the Bayesian networks may also be extremely useful for this kind of multi-traits development, since their dynamic nature makes them particularly adaptable for working in the context of the combination of evidence [30].

8 Conclusion

Nowadays age estimation of living persons is an important practice for many forensic and medico-legal services worldwide. In this paper a Bayesian network for evaluating data coming from the examination of physical attributes has been developed and applied to a hypothetical scenario where an individual is examined by physicians in order to update the belief on the chronological age variable or to evaluate the probability that he is older or not than an age threshold of juridical interest (e.g., 18 years of age). The probabilistic graphical model represents a valuable tool to deal with all uncertainties associated with the process of age estimation; it allows one to produce a posterior distribution on the chronological age as well as posterior probabilities on the propositions of interest.

9 Conflict of Interest

The authors declare they have no conflict of interest.

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Node	Description	Node Type	States
A	Definition of the values of the age variable in intervals of one day for a coherent lifetime.	Interval	0 – 1/365; 1/365 – 2/365; …; 17+364/365 – 18; 18 – 18+1/365; …
H	Chosen hypotheses: the examined individual is older or younger than 18 years of age.	Labelled	>18 ; <18
$C=S_i$	Developmental stages of the clavicle following the classical four-stage classification	Labelled	Stage 1; Stage 2; Stage 3; Stage 4

Table - 1 Definition of the nodes used in the Bayesian network for age estimation

	Regression Parameters	
Transition	**α - Intercept**	**β – Slope**
Stage 1 to 2	18.39	1.35
Stage 2 to 3	21.12	1.17
Stage 3 to 4	30.72	1.30

Table 2 - Results obtained from the application of transition analysis to the data sample presented by Kreitner et al. [34]. A continuation ratio model with logit link was applied for regression analysis.

Node	Description	Node Type	States
α_1, α_2, α_3, β_1, β_2, β_3,	Estimated parameters of the logistic regression	Numbered	α_1=18.39, α_2=21.12, α_3=30.72, β_1=1.35,β_2=1.17, β_3=1.30
Prior - ξ	List of possible values of the location parameter ξ for a skew-normal distribution	Numbered	… 14; 15; 16; …
Prior - ω	List of possible values of the scale parameter ω for a skew-normal distribution	Numbered	… 7; 8; 9; …
Prior - α	List of possible values of the slant parameter α for a skew-normal distribution	Numbered	… 5; 6; 7; …

Table 3 - Definition of the nodes used in the extended structure of the Bayesian network for age estimation.

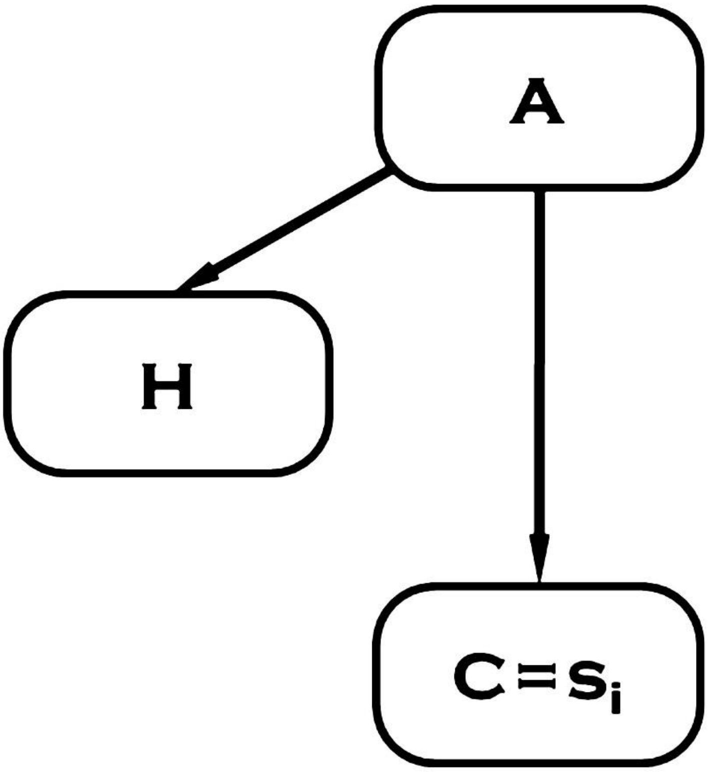

Fig. 1 - Structure for the Bayesian network for age estimation. The node “A” represents the chronological age, while the node “H” the propositions of interest. The last node “C=si” represents the developmental stage assessed during the examination. The definition of the nodes is shown in Table 1.

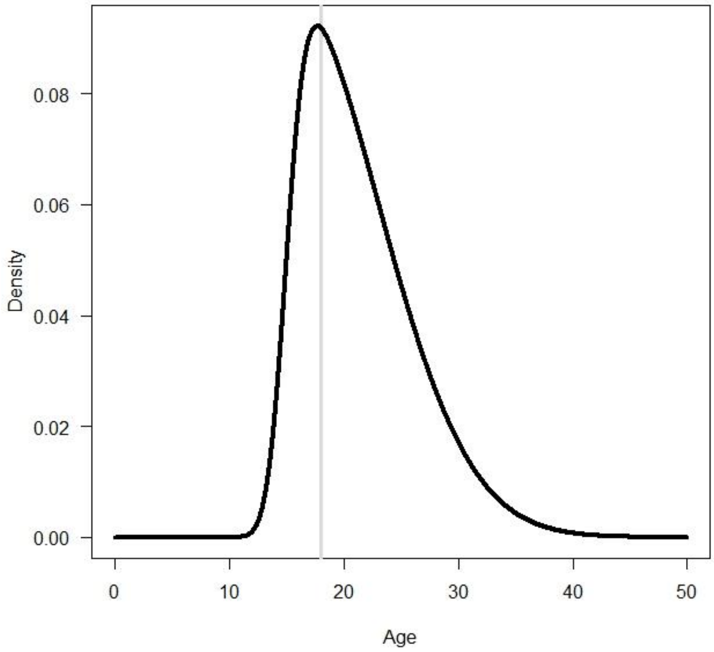

Fig. 2 - The Skew-Normal distribution with location parameter of 15, scale parameter of 8 and slant parameter of 6 used as prior distribution on the chronological age in the examples presented in this paper. The gray vertical line indicates the age of 18 years of age.

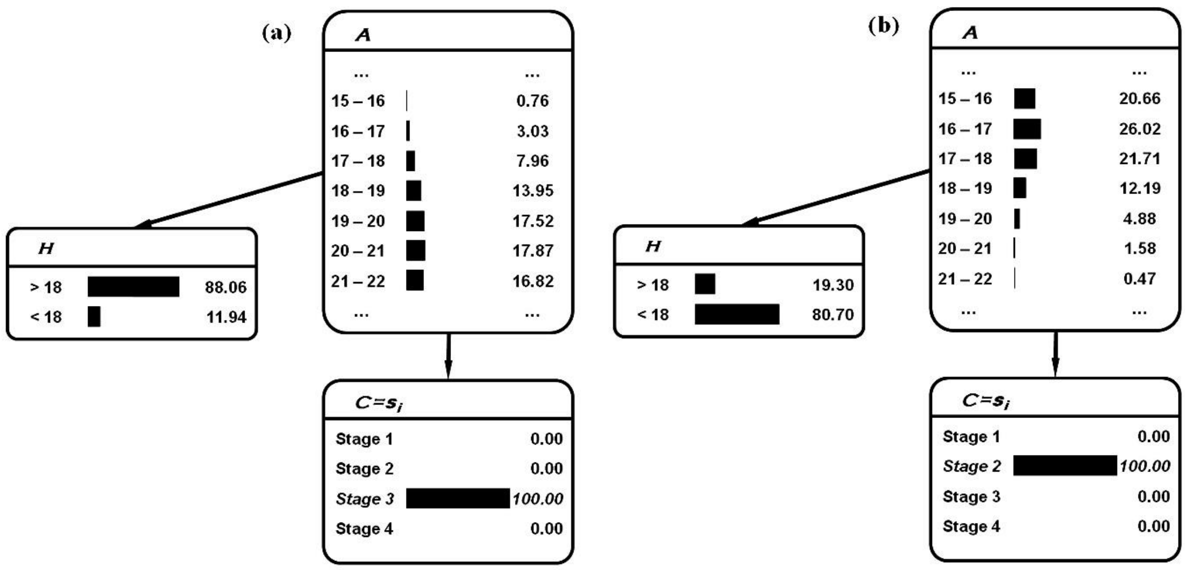

Fig. 3 - Implementation of the Bayesian network for age estimation. Evidence entered into the network is expressed in italics and consists of the instantiation in the node "C=si" of the third (a) and second stages (b) of the four-stage classification for the assessment of the ossification status of the medial clavicle. In the node "A", the posterior probability distribution of the chronological age is partially shown, while the node "H" displays the posterior probability on the propositions of interest. Probability values of each state in the node are shown both graphically and numerically. For the sake of illustration, the states of the node "A" are expressed as one-year intervals in the figure instead of one-day intervals as described in the text.

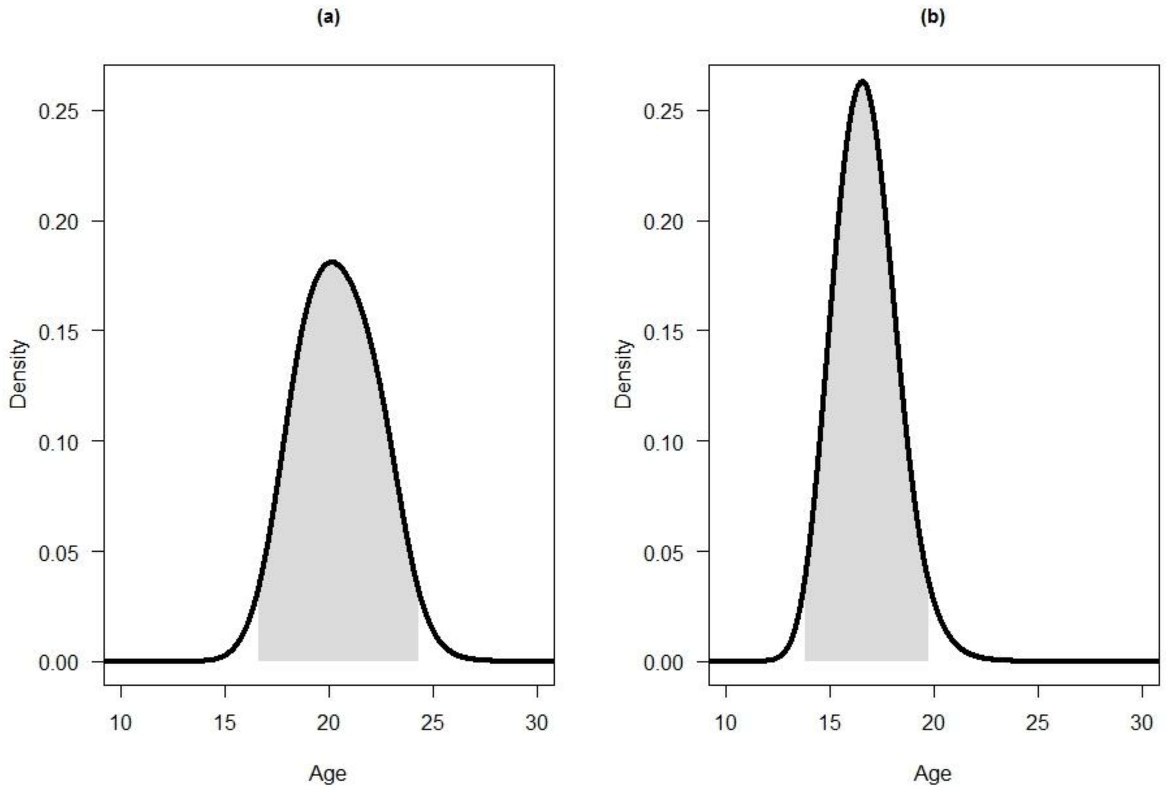

Fig. 4 - The shaded areas under the graphs correspond to the 95% Highest Posterior Density intervals for the posterior probability distributions of the chronological age given the observation of the stages 3 (a) and 2 (b) on the examined individual.

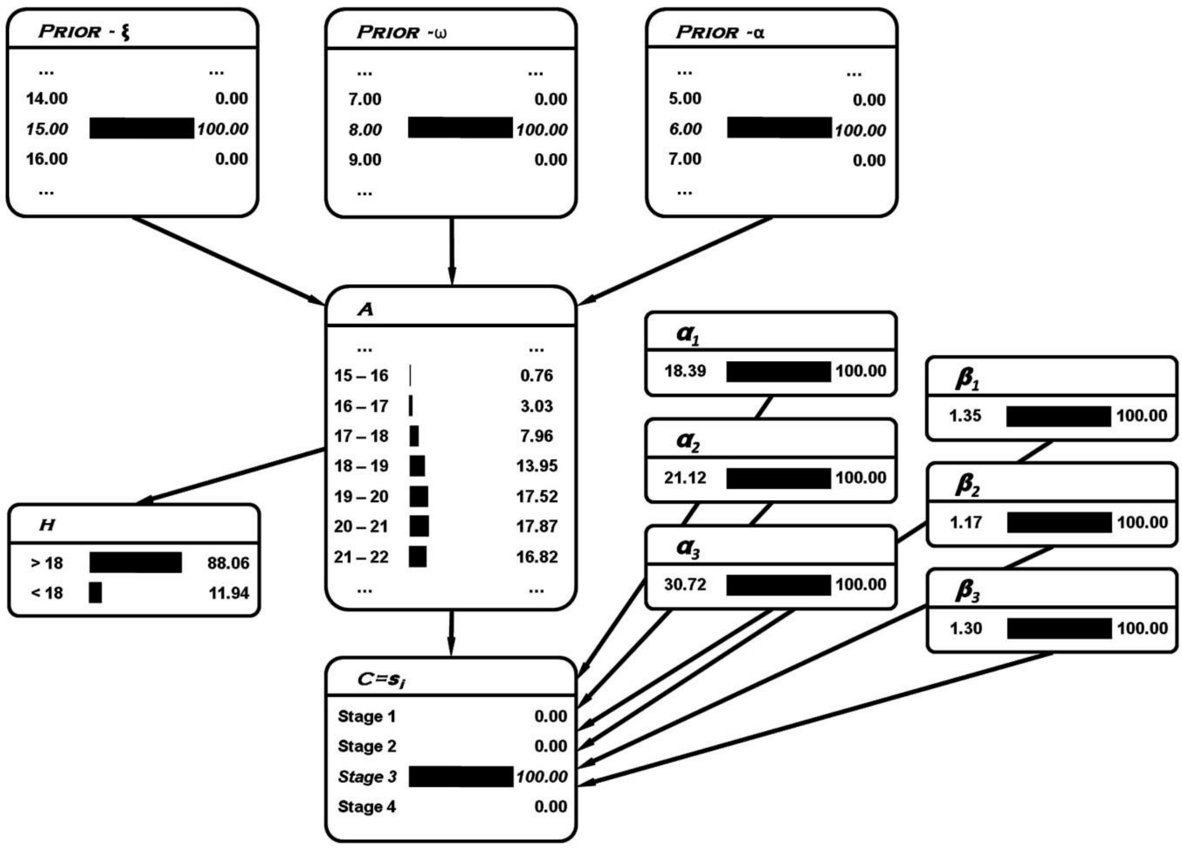

Fig. 5 - Extended structure of the Bayesian network for age estimation. The nodes α1, α2, α3, β1, β2 and β3 represent the regression parameters estimated with transition analysis. The nodes "Prior" model the three parameters of a Skew-Normal distribution. The definition of the nodes is shown in Table 3. Evidence entered into the network is expressed in italics and consists of the instantiation of the third stage of the classification for the assessment of the ossification status of the medial clavicle in the node "C=si". The parameters of the prior distribution (SN(ξ=15, ω=8, α=6)) for the chronological age are also instantiated in the three nodes "Prior". For the sake of illustration, the states of the node "A" are expressed in one-year intervals in the figure instead of one-day intervals as described in the text.